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Measuring the Contribution of Water and Green Space Amenities to Housing Values: An Application and Comparison of Spatially Weighted Hedonic Models

Seong-Hoon Cho, J. M. Bowker, and William M. Park

This study estimates the influence of proximity to water bodies and park amenities on residential housing values in Knox County, Tennessee, using the hedonic price approach. Values for proximity to water bodies and parks are first estimated globally with a standard ordinary least squares (OLS) model. A locally weighted regression model is then employed to investigate spatial nonstationarity and generate local estimates for individual sources of each amenity. The local model reveals some important local differences in the effects of proximity to water bodies and parks on housing price.

Key words: hedonic model, locally weighted regression, park, spatial, water bodies

Introduction

Between 1998 and 2004, 935 out of 1,215 conservation ballot measures in the United States passed, raising close to $25 billion in funding for land conservation in 44 states (The Trust for Public and Land Trust Alliance, 2005). Hence, voters have shown consistent support for open space protection across the United States. A key question, however, is the extent to which public open space is capitalized into nearby residential property values, and thus would increase property tax collections. In some communities, open space protection is linked to water resources as well. For example, in Knox County, Tennessee, community leaders are seeking to protect open space along the French Broad River, an area threatened with development as the sprawling City of Knoxville continues to grow. This initiative is designed to create an open space corridor of river and land that would include a Blueway, equestrian trail, wildlife refuge, historic sites, natural areas, parks, and agricultural land (Knoxville/Knox County Metropolitan Planning Commission, 2003). Estimates of the effect of water and parks on the value of nearby property would be of use in estimating the cost of such initiatives and prioritizing of land parcels to be conserved as open space.

There are two ways to measure these kinds of amenity values. One is to use a survey-based method such as travel cost or contingent valuation. Hedonic pricing is another

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Seong-Hoon Cho is assistant professor and William M. Park is professor, both in the Department of Agricultural Economics, The University of Tennessee. J. M. Bowker is a research social scientist with the USDA Forest Service, Southern Research Station. The authors thank Tim Kuhn and Gretchen Beal of Knoxville/Knox County Metropolitan Planning Commission and Keith G. Stump of Knoxville/Knox County/Knoxville Utilities Board Geographic Information System for providing school district and sales data. The authors also thank co-editor Paul Jakus and two anonymous referees for helpful comments and suggestions.

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approach. Hedonic methods have been gaining popularity in recent years with application of spatial analyses using the geographic information system (GIS). The hedonic price approach has long been used to quantify the impact of open space on residential housing value, including urban parks (Barnett, 1985; Bolitzer and Netusil, 2000; Do and Grudnitski, 1991; Doss and Taff, 1996; Lutzenhiser and Netusil, 2001; Vaughn, 1981) and golf courses (Bolitzer and Netusil, 2000; Lutzenhiser and Netusil, 2001). A common finding in these studies is that green spaces of these types have positive impacts on residential property values up to a distance of one-quarter to one-half mile. As much as 3% of the value of properties could be attributed to park proximity, while proximity to golf courses increased surrounding property values as much as 21%. Recently, McConnell and Walls (2005) reviewed more than 60 published articles that have attempted to estimate the value of different types of open space.

The hedonic property price method also has been used to estimate the value of selected water resources, including lakes and reservoirs, on nearby property values (Brown and Pollakowski, 1977; D'Arge and Shogren, 1989; Darling, 1973; David, 1968; Feather, Pettit, and Ventikos, 1992; Knetsch, 1964; Lansford and Jones, 1995; Reynolds et al., 1973; Young and Teti, 1984). A common finding across these studies is that both the size of lake frontage and lake proximity increase property values. Additionally, the demand for protecting freshwater lakes has been estimated using the hedonic approach (e.g., Boyle, Poor, and Taylor, 1999). In another analysis, seven case studies were undertaken to investigate how much people value groundwater quality and why (Bergstrom, Boyle, and Poe, 2001). Wilson and Carpenter (1999) provide a comprehensive synthesis of peer-reviewed economic data on surface freshwater ecosystems in the United States and examine major accomplishments and gaps in the literature from 1971 to 1997.

While the conceptual logic of the hedonic price approach for capturing the impacts of the green spaces, lakes, and other environmental amenities appears sound, hedonic models are often criticized with regard to specification and calibration issues (Mason and Quigley, 1996; Orford, 2000). Claims of misspecification resulting from missing house value determinants, collinearity among the determinants, and spatial dependency have been made. Furthermore, urban and regional economists have long challenged the assumption of the typical hedonic model that a stationary relationship exists between house prices and housing attributes within a housing market (Adair, Berry, and McGreal, 1996; Goodman and Thibodeau, 1998; Maclennan, 1986; Watkins, 2001; Whitehead, 1999). The critics suggest unitary housing markets might not exist, but rather are composed of interrelated submarkets.

Multilevel modeling techniques are often employed to deal with joint influence of different submarkets (Goodman and Thibodeau, 1995; Jones and Bullen, 1994; Orford, 2000). The multilevel modeling technique defines housing submarkets by structural attributes, geographical location, demander groups, and the joint influence of structural and spatial attributes. Two problems arise, however, with their application. One is the assumption that the exact pattern of nonstationarity in the relationships is known, which demands a priori knowledge and understanding of the local housing market which the researchers are unlikely to have. Second, imposing a discrete set of boundaries on the housing market to identify submarkets may not be realistic because the spatial processes in housing market dynamics are continuous (Fotheringham, Brunsdon, and Charlton, 2002). In addition, necessary data for the multilevel modeling are limited.

The Box-Cox transformation is frequently applied to account for the well-known non-normality of disturbances in hedonic price functions. The Box-Cox model is often estimated with correction for causes of heteroskedasticity (Goodman and Thibodeau, 1995; Fletcher, Gallimore, and Mangan, 2000). However, the Box-Cox model does not correct heteroskedasticity in the disturbances caused by spatial autocorrelation.

In this study, a locally weighted regression approach, as first proposed by Cleveland and Devlin (1988), is adopted to deal with the nonstationarity and spatial autocorrelation issues and allow for estimates of the value of proximity to individual green spaces and water resources. The methodology allows regression coefficients to vary across space in terms of the first law of geography: "Everything is related to everything else, but near things are more related than distant things" (Tobler, 1970, p. 236). No a priori assumption regarding a particular pattern of market nonstationarity is required. The approach has recently been applied intensively to test local heterogeneity (Brunsdon, Fotheringham, and Charlton, 1996, 1999; Fotheringham and Brunsdon, 1999; Fotheringham, Brunsdon, and Charlton, 1998, 2002; Huang and Leung, 2002; Leung, Mei, and Zhang, 2000a, b; Paez, Uchida, and Miyamoto, 2002a, b; Yu and Wu, 2004). To the best of our knowledge, there has been no prior attempt to measure values of multiple spatial attributes at the individual level using the approach in a hedonic property model framework.

The remainder of the paper is organized as follows. First, a brief discussion of the hedonic price model and application of the locally weighted regression methodology within the hedonic price model is presented. Next, the study area, Knox County, Tennessee, and the data are described, followed by a presentation of the analytical results. The paper ends with a summary and concluding remarks.

Methodology

Consider a hedonic model of housing sale prices expressed as:

$$\ln(y_i) = \beta_0 + \sum_k \beta_k x_{ik} + \varepsilon_i, \tag{1}$$

where $\ln(y_i)$ is the natural log of the sale price of a house in a location i; x_{ik} are variables of structural, neighborhood, and location characteristics k; and ε_i is a residual capturing errors. The hedonic model establishes a functional relationship between the observed households' expenditures on housing and these characteristics. Eight key structural characteristics are available and included in this study: total finished square footage, lot size, building age, number of bedrooms, existence of a garage, existence of a fireplace, all sided brick exterior, and existence of swimming pool. In addition to the key characteristics, quality of construction and condition of the structure are included. These two variables are created by six scales—e.g., excellent, very good, good, average, fair, and poor—that are rated by the tax assessors' office. These structural characteristics and quality and condition variables serve as control variables and are typically found to play a large part in explaining housing price variation in the literature. Quadratic specifications for some of the structure variables, such as total finished square footage, lot size, age, and number of bedrooms, are used to capture nonlinear effects (e.g., Bin and Polasky, 2004; Chan, 2004; Mahan, Polasky, and Adams, 2000).

Neighborhood characteristics were reflected primarily by data from the *2000 Census* on median housing value, housing density, average travel time to work, average per capita income, unemployment rate, vacancy rate, and urban versus rural areas at the level of census-block group. The median housing value of census-block group is used to capture direct interdependencies of housing prices in the neighborhoods at the level of census-block group. The further justification for the inclusion of the median housing value is explained by spatial autocorrelation of housing price below. Housing density is included as a measure of how population pressure on land and natural resources affects the housing market (Katz and Rosen, 1987). Average travel time to work is included as a spatial measure of the distance to the employment hub.

Average per capita income and unemployment are included as measures of the relative economic status of a neighborhood (Downs, 2002; Phillips and Goodstein, 2000). Vacancy rate is included as an indicator to capture prevailing housing market conditions (Dowall and Landis, 1982). Another neighborhood variable employed was high school district, as a proxy for school quality. Previous literature has found a positive correlation between school quality with house prices (e.g., Bogart and Cromwell, 1997; Hayes and Taylor, 1996). In addition, dummy variables were included for the town municipalities within the county, the City of Knoxville, and the Town of Farragut. The Knoxville Utilities Board confirmed that there are no community variations with the rates for gas, water, electricity. However, there are differences between the rural and urban areas with regard to public services such as roads and law enforcement. The differences are captured using a dummy variable reflecting urban and non-urban communities.

Location variables included distance to downtown Knoxville; distances to the nearest water body, greenway, railroad, and park; and size of nearest park. These distance variables are intended to capture the effect on housing prices of the proximity to various amenities and disamenities. The size of nearest park variable is intended to capture the premium being closer to the bigger park. Park size has been found to be a significant factor on property value (Lutzenhiser and Netusil, 2001). Similarly, variables reflecting quality of water bodies and floodplain area might capture amenity or disamenity effects of being closer to water bodies. A dummy variable, indicating whether or not there is any impairment incident reported by the Environmental Protection Agency (2005), is included. To separate any floodplain effect from the effect of proximity to a water body, a dummy variable for location in a stream protection area (representing all of the flood fringe area of the 500-year flood plain) in the county is created and included in the model.

Previous studies have found that a log transformation of distance variables generally performs better than a simple linear functional form because the log transformation captures the declining effect of these distance variables (Bin and Polasky, 2004; Iwata, Murao, and Wang, 2000; Mahan, Polasky, and Adams, 2000). A log transformation of the quadratic specifications for some of the structure variables was attempted, but the transformation was not found to improve the model. Thus, a natural log transformation for distance-related variables and median housing value are used in this study.

Findings of earlier analyses indicate the mortgage interest rate is a significant driver of housing price dynamics (e.g., Tsatsaronis and Zhu, 2004). Yearly prime interest rates from the website of the Board of Governors of the Federal Reserve System (2006), which represent mortgage interest rates for the year of the sale transaction, were converted to real interest rates by subtracting the annual change in the consumer price index.

House prices are also believed to vary seasonally—i.e., prices are higher in spring and summer irrespective of the overall trend. More buyers tend to be in the market during the spring and summer, pushing the demand curve to the right and increasing the equilibrium housing price. A seasonal dummy is included to capture the expected difference in housing prices between spring/summer and fall/winter.

Heteroskedasticity often occurs in cross-section data when there is a wide range in the explanatory variables. A log transformation is one way in which heteroskedasticity can be removed, because this transformation reduces the variation in the variables. However, taking the logs may not prevent the problem. Thus, the Breusch-Pagan Lagrange multiplier test was conducted for heteroskedasticity in the error distribution, conditional on a set of variables which are presumed to influence the error variance. The test statistic, a Lagrange multiplier measure, has a Chi-squared distribution under the null hypothesis of homoskedasticity. Sometimes the form of the heteroskedasticity is clear and can be modeled. More commonly, though, heteroskedasticity is a nuisance that cannot be modeled because its source is not well understood. Long and Ervin (2000) suggest that the approach using a heteroskedasticity-consistent covariance matrix proposed by MacKinnon and White is the best. In *Stata 9.1* (StataCorp LP, 2005), the HC3 option is used in the REG command for the calculation of the consistent estimator in the presence of heteroskedasticity of an unknown form.

Another concern in regression models with many explanatory variables is multicollinearity, which occurs when two (or more) independent variables are linearly related. Multicollinearity can seriously inflate the standard errors of the estimates and render hypothesis testing inconclusive. If the correlation coefficient between two regressors is greater than 0.8 or 0.9, multicollinearity may be a serious problem (Judge et al., 1982, p. 620). Multicollinearity can also be detected by variance inflation factors (Maddala, 1992). Variance inflation factors (vif's) are a scaled version of the multiple correlation coefficients between variable k and the rest of the independent variables. Specifically, $vif_k = 1/(1 - R_k^2)$, where R_k is the multiple correlation coefficient. There is no clear guideline for how large *vif* must be to reflect serious multicollinearity. The variables removed from the initial model because of potential problems with multicollinearity were distance to nearest golf course and distance to the Great Smoky Mountains National Park. Both variables are highly correlated with another variable (distance to park), with correlation coefficients greater than 0.6 and vif's greater than 10.0.

Global Moran's Index (Moran, 1948) is used to measure spatial autocorrelation in sale price of a house variable. The index is a measure of the overall spatial relationship across geographical units and is defined as:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\left(\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \right) \sum_{i=1}^{n} (y_i - \bar{y})^2},$$

where n is the sample size, y_i is the sale price of a house i with sample mean $\bar{y}$, and w_{ij} is the distance-based weight which is the inverse distance between houses i and j. Like a correlation coefficient, a positive Moran's value stands for positive spatial autocorrelation, e.g., similar, regionalized, or clustered observations, zero (approximately in finite samples) for a random pattern, and negative value for negative spatial autocorrelation (for instance, a dissimilar, contrasting pattern) (Goodchild, 1986, pp. 16–17). As spatial autocorrelation is detected in the house sale price variable, median housing value at the census-block group level is included to control spatial autocorrelation in the model.

Equation (1) can be considered a global model, in contrast to the locally weighted regression. The partial derivatives of the hedonic price function with respect to each characteristic in the global model yield an overall marginal implicit price. For example, the first partial derivative for the characteristic distance to the nearest park represents the added value associated with being located one unit closer to the nearest park overall. It is important to note that this marginal implicit price for the nearest park overall is essentially an average across all parks in the study area. The willingness to pay (WTP) for increased proximity to any particular individual park is not revealed in the global model. This is especially troubling if the attributes of parks are not homogeneous in a given area.

We estimate the following hedonic price equation for the locally weighted regression using the GWR 3.0 software developed by Fotheringham, Brunsdon, and Charlton (2002):

$$\ln(y_i) = \beta_0(u_i, v_i) + \sum_k \left[\beta_k(u_i, v_i)x_{ik}\right] + \varepsilon_i,$$

where (u_i, v_i) denotes the coordinates of the ith point in space, and $\beta_k(u_i, v_i)$ is a realization of the continuous function $\beta_k(u, v)$ at point i. Specifically, we allow a continuous surface of parameter values, and measurements of this surface are taken at certain points to denote the spatial variability of the surface (Fotheringham, Brunsdon, and Charlton, 2002).

Calibration of the locally weighted regression model follows a local weighted least squares approach. Different from OLS, the locally weighted regression assigns weights according to their spatial proximity to location i in order to account for the fact that an observation near location i has more of an influence in the estimation of the various $\beta_k(u_i, v_i)$ than do observations located farther from i. That is,

$$\hat{\beta}(u_i, v_i) = \left(\mathbf{X}^T\mathbf{W}(u_i, v_i)\mathbf{X}\right)^{-1}\mathbf{X}^T\mathbf{W}(u_i, v_i)\mathbf{Y},$$

where $\hat{\beta}$ represents an estimate of β; $\mathbf{X}$ is a vector of the variables of structural, neighborhood, and location characteristics $\ln(x_{ik})$; $\mathbf{Y}$ is a vector of $\ln(y_i)$; $\mathbf{W}(u_i, v_i)$ is an $n \times n$ diagonal matrix with diagonal elements w_{ii} denoting the geographical weighting of observed data point for location i.

To better understand how locally weighted regression operates, consider the locally weighted regression equivalent of the classical regression equation,

$$\mathbf{Y} = (\beta \otimes \mathbf{X})\mathbf{1} + \varepsilon,$$

where $\otimes$ is a logical multiplication operator in which each element of β is multiplied by the corresponding element of $\mathbf{X}$, and $\mathbf{1}$ is a conformable vector of 1's. If there are n data points and k explanatory variables including the constant term, both β and $\mathbf{X}$ will have dimensions $n \times k$. The matrix β now consists of n sets of local parameters and has the following structure:

$$\beta = \begin{bmatrix} \beta_0(u_1, v_1) & \beta_1(u_1, v_1) & \cdots & \beta_k(u_1, v_1) \\ \beta_0(u_2, v_2) & \beta_1(u_2, v_2) & \cdots & \beta_k(u_2, v_2) \\ \cdots & \cdots & \cdots & \cdots \\ \beta_0(u_n, v_n) & \beta_1(u_n, v_n) & \cdots & \beta_k(u_n, v_n) \end{bmatrix}.$$

$\mathbf{W}(i)$ is an $n \times n$ spatial weighting matrix of the form

$$\mathbf{W}(i) = \begin{bmatrix} w_{i1} & 0 & \dots & 0 \\ 0 & w_{i2} & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & w_{in} \end{bmatrix},$$

where w_{ij} is the weight given to data point j in the calibration of the model for location i. The diagonal elements of the weight matrix, w_{ij}, are equal to:

$$w_{ij} = \begin{cases} \left[1 - (d_{ij}/b)^2\right]^2 & \text{if } d_{ij} < b, \\ 0 & \text{otherwise,} \end{cases}$$

where d_{ij} is the Euclidean distance between points i and j, and b is a chosen bandwidth.[1] At the regression point i, the weight of the data point is unity and falls to zero when the distance between i and j equals the bandwidth or higher.

As b tends to be infinity, w_{ij} approaches 1 regardless of d_{ij}, in which case the parameter estimates become uniform and locally weighted regression is equivalent to OLS. Conversely, as b becomes smaller, the parameter estimates will increasingly depend on observations in close proximity to location i, and hence have increased variance. A cross-validation (CV) approach is suggested for local regression for a selection of optimal bandwidth (Cleveland, 1979). CV takes the following form:[2]

$$CV = \sum_{i=1}^{n} \left[y_i - \hat{y}_{\neq i}(b)\right]^2, \tag{2}$$

where $\hat{y}_{\neq i}(b)$ is the fitted value of y_i with the observations for point i omitted from the fitting process. The bandwidth is chosen to minimize CV. Thus, in the local weighted regression model, only houses up to the optimal level of b are assigned nonzero weights for the nearest neighbors of census-block group i. The weight of these points will decrease with their distance from the regression point. Sensitivity analysis was conducted for bandwidths of plus and minus 50% of the b selected by the CV approach.

Because the local model allows regression coefficients to vary across space, the spatially varying partial derivative of the hedonic price function with respect to any characteristic is estimated locally. Measuring the spatially varying partial derivative of the hedonic price function with respect to any characteristic allows us to quantify the local value of that characteristic individually. For example, the first partial derivative of the nearest park in the local model can be used to calculate a marginal implicit price of proximity to that specific park individually. The local marginal implicit prices of individual parks are summarized to show the variation in values of different parks.

[1] The choice of bandwidth represents a tradeoff between bias (which increases with bandwidth), and variance of the estimates from the data (which decreases with bandwidth).

[2] This process is almost identical to choosing b on a "least squares" criterion except for the fact that the observation for point i is omitted.

Study Area and Data

Knox County is located in East Tennessee, one of the state's three "Grand Divisions." Knoxville is the county seat of Knox County. The City of Knoxville comprises 101 square miles of the 526 total square miles in Knox County. Downtown Knoxville is 936 feet above sea level. The Great Smoky Mountains National Park, the most-visited national park in the country, is less than 15 miles away, and the county is surrounded by several Tennessee Valley Authority lakes.

The county has been growing rapidly in recent years. During the 1980s, the population of Knox County increased by 5%. During the following decade, the rate of population growth nearly tripled to 14%, rising from 335,749 to 382,032 residents. Most of the recent rapid growth in the county has occurred in portions of west and north Knox County, while other areas have seen slow growth or decline. Specifically, population in the Southwest and Northwest County Sectors, as defined by the Knoxville/Knox County Metropolitan Planning Commission (MPC), gained 36% and 29%, respectively, in the 1990s, accounting for about two-thirds of the countywide increase. The county has 40 local parks. There are 25 perennial streams and rivers, 49 perennial lakes and ponds, two perennial reservoirs, and seven water bodies classified as an unknown water feature based on the U.S. Census Bureau's Census Feature Class Codes.

This study employs three data sets: (*a*) parcel records from Knoxville/Knox County/ Knoxville Utilities Board (KUB) Geographic Information System (KGIS), (*b*) 2000 census-block group, and (*c*) geographical information from 2004 Environmental Systems Research Institute (ESRI) maps and data. The three data sets are all geographically digitalized. Property parcel records contain detailed information about the structural attributes of properties, the census-block group data describe neighborhood characteristics, and the ESRI data describe distance characteristics.

Data were used for single-family houses sold between 1998 and 2002 in Knox County, Tennessee. A total of 22,704 single-family housing sales transactions were undertaken during this period. Of the 22,704 houses sold, 15,500 were randomly selected for analysis (see figure 1). Housing sale prices were adjusted to 2000 dollars to account for real estate market fluctuations in the Knoxville metro region.[3] This adjustment was made using the annual housing price index for the Knoxville metropolitan statistical area obtained from the Office of Federal Housing Enterprise Oversight. Knox County consists of 234 census-block groups. Information from 2000 census-block groups was assigned to houses located within the boundaries of the block groups. The timing cycle of the census and sales records did not match except in 2000. However, given the periodic nature of census taking, census data for 2000 were considered proxies for real-time data for 1998, 1999, 2001, and 2002. Distance calculations for various location variables were made using the shape files and ArcGIS 9.1.

Variable names, definitions, and descriptive statistics for the variables used in the estimations are presented in table 1. It should be noted that house prices below $40,000 were eliminated from the sample data. County officials suggested the sale prices below $40,000 probably were associated with gifts, donations, and inheritances, and thus would not reflect true market value. Officials also indicated that the parcel records smaller than 1,000 square feet were suspect; consequently, parcels smaller than 1,000 square feet were eliminated from the sample data. The final sample used for estimation

[3] Housing sale prices were adjusted to 2000 dollars to conform with the 2000 census-block group information.

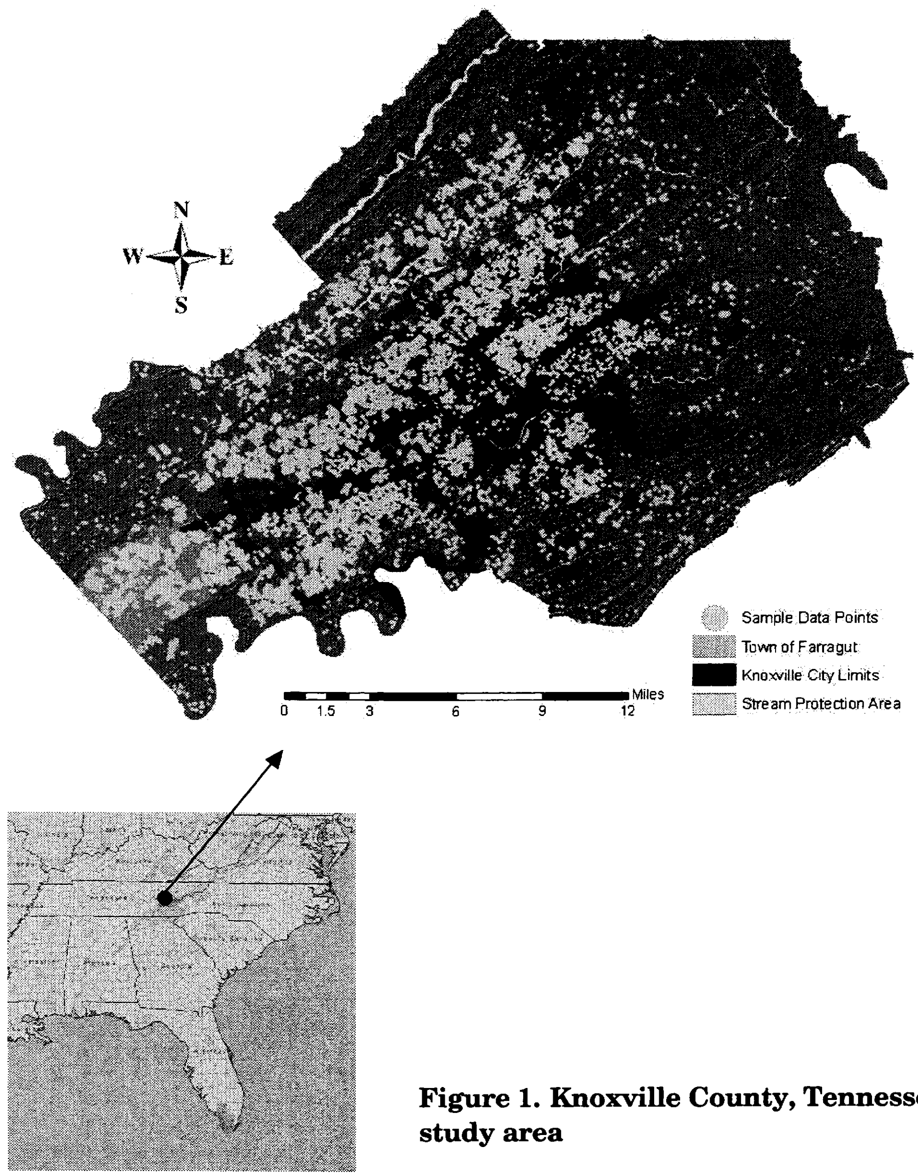

Figure 1. Knoxville County, Tennessee, study area

contained 15,335 observations.[4] The average selling price was $129,610 in 2000 dollars, with a maximum of $1,824,530. A typical sample home is about 29 years old and has 1,930 square feet of finished area, 25,896 square feet or 0.59 acres of lot area, and three bedrooms. About 73% of the sample homes have a fireplace, approximately 25% have all brick exterior walls, about 6% have a pool, and about 64% have a garage. Average travel time to work is 23 minutes, average per capita income is $25,233, and the average unemployment rate is 4%.

[4] Selecting a random sample of sales transactions saved time in running the locally weighted regression, which took 72 hours for each run with 15,335 observations.

Table 1. Variable Name, Definition, and Descriptive Statistics

Variable	Unit	Definition	Mean	Std. Dev.
Dependent Variable				
Housing Price	$	House sale price adjusted to the 2000 housing price index	129,610.227	95,460.498
Structural Variables:				
Finished Area	square feet	Total finished structure square footage	1,929.689	975.633
Lot Size	square feet	Lot square footage	25,895.720	69,956.690
Age	year	Year house was built subtracted from 2006	29.207	21.733
Bedroom		Number of bedrooms	3.068	0.647
Garage		Dummy variable for garage (1 if garage; 0 otherwise)	0.635	0.481
Fireplace		Dummy variable for fireplace (1 if fireplace; 0 otherwise)	0.729	0.575
Brick		Dummy variable for all brick (1 if all brick; 0 otherwise)	0.254	0.435
Pool		Dummy variable for pool (1 if pool; 0 otherwise)	0.055	0.229
Quality of Construction		Dummy variable for quality of construction (1 if excellent, very good, and good; 0 otherwise)	0.352	0.478
Condition of Structure		Dummy variable for condition of structure (1 if excellent, very good, and good; 0 otherwise)	0.734	0.442
Census-Block Group Variables:				
Median Housing Value	$	Median housing value for census-block group reported in 2000	120,874.751	52,634.422
Housing Density	houses/acre	Housing density for census-block group in 2000	1.105	0.927
Travel Time to Work	minutes	Average travel time to work for census-block group in 2000	22.519	3.314
Per Capita Income	$1,000s per resident	Per capita income for census-block group in 2000	25.233	10.028
Unemployment Rate	ratio	Unemployment rate for census-block group in 2000	0.037	0.029
Vacancy Rate	ratio	Vacancy rate for census-block group in 2000	0.063	0.031
High School Dummy Variables:				
Bearden		Dummy variable for Bearden high school district (1 if Bearden; 0 otherwise)	0.157	0.363
Carter		Dummy variable for Carter high school district (1 if Carter; 0 otherwise)	0.027	0.161
Central		Dummy variable for Central high school district (1 if Central; 0 otherwise)	0.092	0.290
Doyle		Dummy variable for Doyle high school district (1 if Doyle; 0 otherwise)	0.077	0.266
Fulton		Dummy variable for Fulton high school district (1 if Fulton; 0 otherwise)	0.053	0.224
Gibbs		Dummy variable for Gibbs high school district (1 if Gibbs; 0 otherwise)	0.055	0.228
Halls		Dummy variable for Halls high school district (1 if Halls; 0 otherwise)	0.057	0.231

(continued . . .)

Table 1. Continued

Variable	Unit	Definition	Mean	Std. Dev.
High School Dummy Variables (cont'd.):				
Karns		Dummy variable for Karns high school district (1 if Karns; 0 otherwise)	0.147	0.354
Powell		Dummy variable for Powell high school district (1 if Powell; 0 otherwise)	0.065	0.247
Austin		Dummy variable for Austin high school district (1 if Austin; 0 otherwise)	0.014	0.116
Farragut		Dummy variable for Farragut high school district (1 if Farragut; 0 otherwise)	0.148	0.355
Jurisdiction Dummy Variable:				
Knoxville		Dummy variable for City of Knoxville (1 if Knoxville; 0 otherwise)	0.343	0.475
Distance Variables:				
Downtown	feet	Distance to downtown Knoxville	44,552.592	20,713.081
Water Body	feet	Distance to nearest stream, lake, or river	8,440.579	5,884.047
Greenway	feet	Distance to nearest greenway	7,886.866	5,573.062
Railroad	feet	Distance to nearest railroad	6,978.618	5,463.655
Park	feet	Distance to nearest local park	8,652.930	5,556.530
Other Variables:				
Park Size	1,000 acres	Size of nearest local park	0.033	0.117
Impairment		Dummy variable for impairment incident by EPA on nearest stream, lake, or river	0.453	0.870
Prime Interest Rate	percentage	Average price interest rate less average inflation rate	4.267	2.104
Season		Dummy variable for season of sale (1 if spring or summer; 0 otherwise)	0.559	0.497
Urban		Dummy variable for urban/rural area (1 if a house is located in census block of 100% urban housing; 0 otherwise)	0.777	0.417
Flood		Dummy variable for flood area (1 if a house is located in stream protection area; 0 otherwise)	0.010	0.097

Estimation Results

The results of the global model and local model are presented in table 2. The adjusted R^2 value for the global model is 0.74, while for the local model it is 0.76. The local model also reduces the residual sum of squares from 1,146 in the global model to 1,044. The improved adjusted R^2 and lower residual sum of squares suggest the local model fits the data better than the global model. The positive and statistically significant variable for the median housing value of the census-block group shows that the variable corrects for spatial autocorrelation of the housing price. The variable captures spatial spillover of housing value in the neighborhood at the level of census-block group.

The results from the global model show that all of the structural variables are statistically significant at the 1% level. Coefficient signs of the structural variables are as intuitively expected. Evaluated at the average house value, the results indicate that

Table 2. Parameter Estimates of Global and Local Models [dependent variable = ln(*Housing Price*)]

	GLOBAL MODEL		LOCAL MODEL				
Variable	Coefficient	Std. Error	Minimum	Lower Quartile	Median	Upper Quartile	Maximum
Intercept	9.553***	0.160	7.581	8.786	9.371	9.944	11.301
Structural Variables:							
Finished Area / 1,000s, sq. ft.	0.302***	0.005	0.296	0.329	0.355	0.410	0.506
(*Finished Area* / 1,000s, sq. ft.)^2	-0.012***	0.000	-0.047	-0.031	-0.022	-0.012	-0.010
Lot Size / 100,000s, sq. ft.	0.081***	0.006	0.043	0.128	0.180	0.232	0.388
(*Lot Size* / 100,000s, sq. ft.)^2	-0.002***	0.000	-0.099	-0.030	-0.018	-0.010	-0.001
Age	-0.012***	0.000	-0.023	-0.016	-0.013	-0.010	-0.009
Age^2	0.000***	0.000	0.000	0.000	0.000	0.000	0.000
Bedroom	0.090***	0.016	0.018	0.082	0.103	0.125	0.188
Bedroom^2	-0.009***	0.002	-0.028	-0.016	-0.012	-0.007	0.001
Garage	0.076***	0.005	0.060	0.067	0.076	0.078	0.101
Fireplace	0.062***	0.005	0.013	0.035	0.049	0.058	0.081
Brick	0.057***	0.006	0.015	0.035	0.042	0.061	0.083
Pool	0.068***	0.010	0.012	0.024	0.061	0.093	0.126
Quality of Construction	0.164***	0.006	0.092	0.130	0.146	0.179	0.214
Condition of Structure	0.087***	0.006	0.039	0.063	0.075	0.090	0.140
Census-Block Group Variables:							
ln(*Median Housing Value*)	0.096***	0.011	-0.090	0.040	0.073	0.136	0.280
Housing Density	0.001	0.003	-0.049	-0.030	-0.007	0.003	0.024
Travel Time to Work	0.002*	0.001	-0.005	0.000	0.002	0.005	0.009
Per Capita Income / $1,000s	0.006***	0.000	-0.003	0.004	0.006	0.007	0.009
Unemployment Rate	-0.080	0.094	-0.763	-0.177	-0.098	0.039	1.309
Vacancy Rate	0.063	0.091	-0.282	-0.012	0.044	0.496	1.274
High School Dummy Variables:							
Bearden	-0.043***	0.012	-0.344	-0.049	0.000	0.000	0.359
Carter	-0.068***	0.018	-0.610	-0.069	0.000	0.000	0.184
Central	-0.045***	0.011	-0.225	-0.038	0.000	0.000	0.557

(continued . . .)

Table 2. Continued

	Global Model		Local Model				
Variable	Coefficient	Std. Error	Minimum	Lower Quartile	Median	Upper Quartile	Maximum
High School Dummy Variables (cont'd.):							
Doyle	-0.044***	0.015	-0.249	-0.057	0.000	0.000	0.821
Fulton	-0.076***	0.014	-0.233	-0.051	0.000	0.000	0.069
Gibbs	-0.086***	0.016	-0.319	-0.167	0.000	0.000	0.170
Halls	-0.034**	0.015	-0.270	-0.105	0.000	0.000	1.394
Karns	-0.037***	0.012	-0.241	-0.036	-0.011	0.004	0.235
Powell	-0.028**	0.014	-0.980	-0.118	-0.037	0.000	0.206
Austin	-0.188***	0.024	-0.527	-0.127	0.000	0.000	0.140
Farragut	-0.105***	0.016	-0.265	-0.052	0.000	0.000	0.395
Jurisdiction Dummy Variable:							
Knoxville	-0.017*	0.009	-0.153	-0.084	-0.029	0.010	0.097
Distance Variables:							
ln(*Downtown*)	0.032**	0.014	-0.167	-0.024	0.026	0.077	0.224
ln(*Water Body*)	-0.020***	0.003	-0.081	-0.027	-0.013	0.006	0.033
ln(*Greenway*)	-0.015***	0.003	-0.022	-0.011	-0.001	0.006	0.022
ln(*Railroad*)	0.004	0.003	-0.019	-0.001	0.010	0.020	0.039
ln(*Park*)	-0.007**	0.003	-0.030	-0.019	-0.012	0.000	0.038
Other Variables:							
Park Size / 1,000s, acres	0.010	0.021	-0.404	-0.131	0.109	1.355	2.282
Impairment	0.003	0.003	-0.022	-0.006	0.007	0.019	0.042
Prime Interest Rate	0.003**	0.001	-0.003	0.001	0.003	0.004	0.010
Season	0.024***	0.004	0.000	0.016	0.023	0.028	0.045
Urban	0.034***	0.008	-0.018	0.014	0.049	0.091	0.222
Flood	-0.027	0.023	-0.122	-0.045	0.009	0.041	0.140
Adjusted R^2	0.74				0.76		

Notes: Single, double, and triple asterisks (*) denote statistical significance at the 10%, 5%, and 1% levels, respectively. Sample size is 15,335 and bandwidth is 19,204 feet.

house price increases by $39 per additional square foot of finished area. An additional 1,000 square feet of parcel size increases sale price by $104. The marginal implicit price of increasing the age of a house by one year, evaluated at the mean house value, yields an estimate of $1,555 in decreased house value. Having an additional bedroom increases estimated sale price by $11,664. A garage increases sale price by $9,850, a fireplace by $8,036, and a brick exterior by $7,387. A 1% point increase in the prime interest rate increases the estimated sale price by $388. The positive relationship between interest rate and housing price is counterintuitive. However, this relationship depends on whether interest rates rise due to inflationary expectations (the rate of increase in the general price level anticipated by the public in the period ahead) or because real rates are rising due to an increased demand for credit. If it is the former, housing prices can continue to rise even as interest rates rise (Kling, 2004). The coefficient of the seasonal dummy variable shows that, on average, spring and summer sale prices are $3,111 higher than fall and winter sale prices. Everything else constant, a house in an area considered to be urban can be sold for a $4,407 premium.

The coefficients of census-block group variables, median housing value and per capita income, are of the predicted sign with statistical significance at the 1% level. Evaluated at the average house value of $129,610, 10% of the fluctuation in housing price is due to neighborhood effect. Since location characteristics are considered to be paramount in determining real estate value, a strong neighborhood effect seems to be reasonable. Evaluated at the average house value, house price increases by $778 per additional $1,000 of per capita income. The local model shows that the marginal effects of per capita income vary somewhat across the study area.

All 11 high school dummy variables are statistically significant at the 5% level or better. Note that there are 12 high school districts in Knox County, and the town of Farragut coincides with the Farragut high school district. The reference district used for the high school dummy variables is the West high school district. School district dummy variables with negative effects have relatively lower average American College Testing (ACT) scores than the West high school district except for the Farragut and Austin high school districts. The signs of all but two dummy variables are consistent with previous research about school accountability ratings and housing value (Kane, Staiger, and Samms, 2003). The negative coefficient for Knoxville, the jurisdiction dummy variable, indicates house price is higher if the house is located outside the city boundary of Knoxville. Though other factors may contribute, this relationship is likely due to the perception that the value of additional public services provided to property owners within the city limits does not fully compensate for the higher city property taxes.

Coefficient signs for the distance variables are as expected. Although the coefficient for the distance to railroad variable is not statistically significant in the global model, the local model shows that more than 50% of the coefficients have positive signs, suggesting that in some areas house price increases with increasing distance from railroad. This is likely due to noise disamenities or inconvenience. The coefficients for the distances to downtown, water body, greenway, and park are statistically significant at the 5% level or better in the global model. Evaluated at the mean house price of 129,610 and an initial distance of one mile, moving 1,000 feet closer to water bodies increases the average house price by $491. Moving 1,000 feet closer to the nearest park increases the average house price by $172, while reducing the distance to the nearest greenway by 1,000 feet increases house value by $368. The variable for park size is not

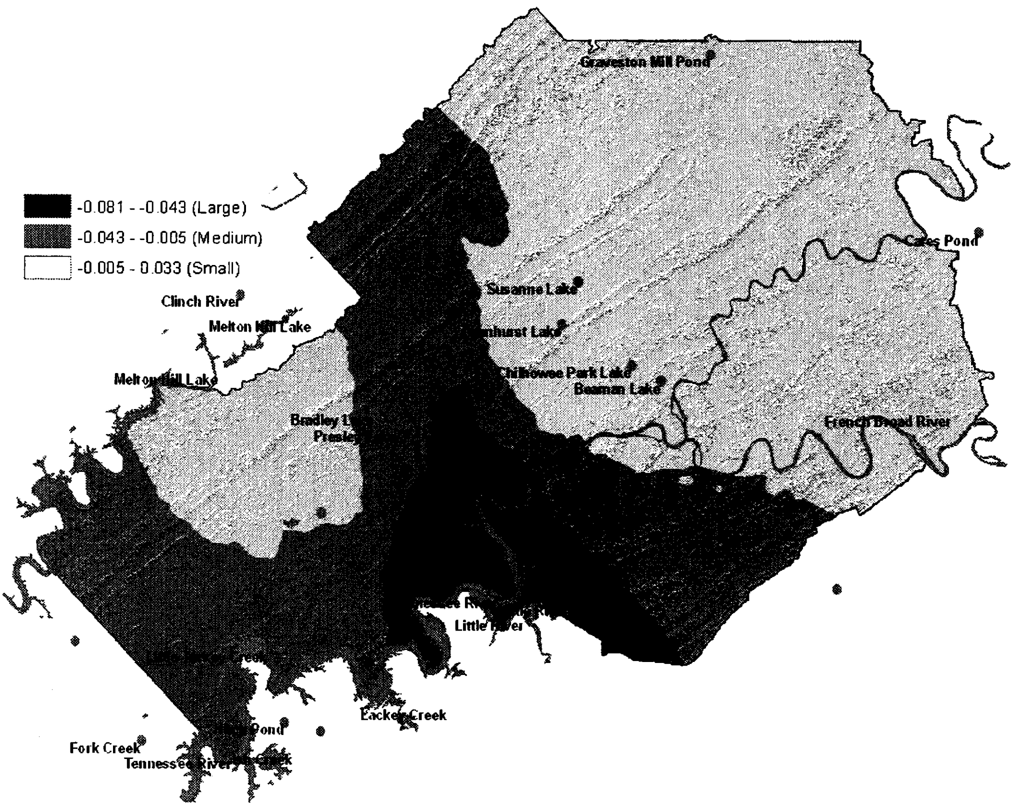

Figure 2. Spatial distribution of marginal effect of distance to nearest water body on house price

statistically significant in the global model, though the local model suggests the effects of park size may be positive in some areas. The impairment and flood dummy variables are found to be insignificant.

Figure 2 shows the locations of the water bodies and spatial variation in the marginal effects of proximity to water bodies. Table 3 reports the summary results of the average local marginal implicit price of proximity to water bodies. As shown by the figure and the table, the marginal effects of proximity to water bodies in the southwest region of the county near the Tennessee River are higher than in other regions of the county. Both marginal effect and marginal implicit price decrease as one moves away from this region of the county. In fact, house prices in the east and northeast regions show a small negative effect from being closer to water bodies. One explanation for this variation is that the cluster of larger positive effects is in an area where the water bodies are large enough to offer beautiful scenic vistas (the Tennessee River and a major tributary). In contrast, the cluster of marginal effects close to zero is an area where water bodies are generally small creeks and small lakes or ponds, which offer little in the way of scenic vistas.

Figure 3 shows the location of the parks and spatial variation in the marginal effects of proximity to the parks. The summary results of the average local marginal implicit

Table 3. Mean Water Body Values Using Estimates from the Local Model

Water Body	Mean Marginal Effect	Mean House Price ($)	Mean Water Body Value ($)	N
Little River	-0.080	398,143	6,032	8
Tennessee River	-0.058	231,538	2,543	285
Sterchi Lake	-0.029	347,198	1,907	1
Holder Branch	-0.027	335,834	1,717	3
Fleniken Branch	-0.058	101,758	1,118	16
Sinking Creek	-0.028	208,990	1,108	824
Stock Creek	-0.049	119,150	1,106	134
Little Turkey Creek	-0.021	229,583	913	627
Hickory Creek	-0.019	248,036	893	197
Knob Creek	-0.049	87,374	811	47
Jolly Giant Lake	-0.030	126,454	718	246
Fort Loudoun Lake	-0.027	140,378	718	1,321
Tobler Lake	-0.030	101,918	579	27
Presley Lake	-0.030	96,734	550	1,216
Turkey Creek	-0.017	158,282	510	539
Bradley Lake	-0.020	108,886	412	225
3rd Creek	-0.017	89,170	287	14
French Broad River	-0.013	82,058	202	358
Melton Hill Lake	-0.007	123,485	164	375
Lynnhurst Lake	0.003	80,789	-46	1,094
Graveston Mill Pond	0.003	91,072	-52	29
Susanne Lake	0.003	116,578	-66	1,789
Reservoir	0.007	60,661	-80	21
Beaman Lake	0.007	64,403	-85	47
Clinch River	0.003	151,340	-86	313
Holston River	0.005	91,827	-87	486
Chilhowee Park Lake	0.007	69,897	-93	410
Armstrong	0.005	118,971	-113	93
Bud Hodge Lake	0.007	118,238	-157	358
Dead Horse Lake	0.021	124,922	-497	722

Notes: The mean water body value is the marginal implicit price for reducing the distance to the nearest water body by 1,000 feet, evaluated at the mean house value and an initial distance of one mile.

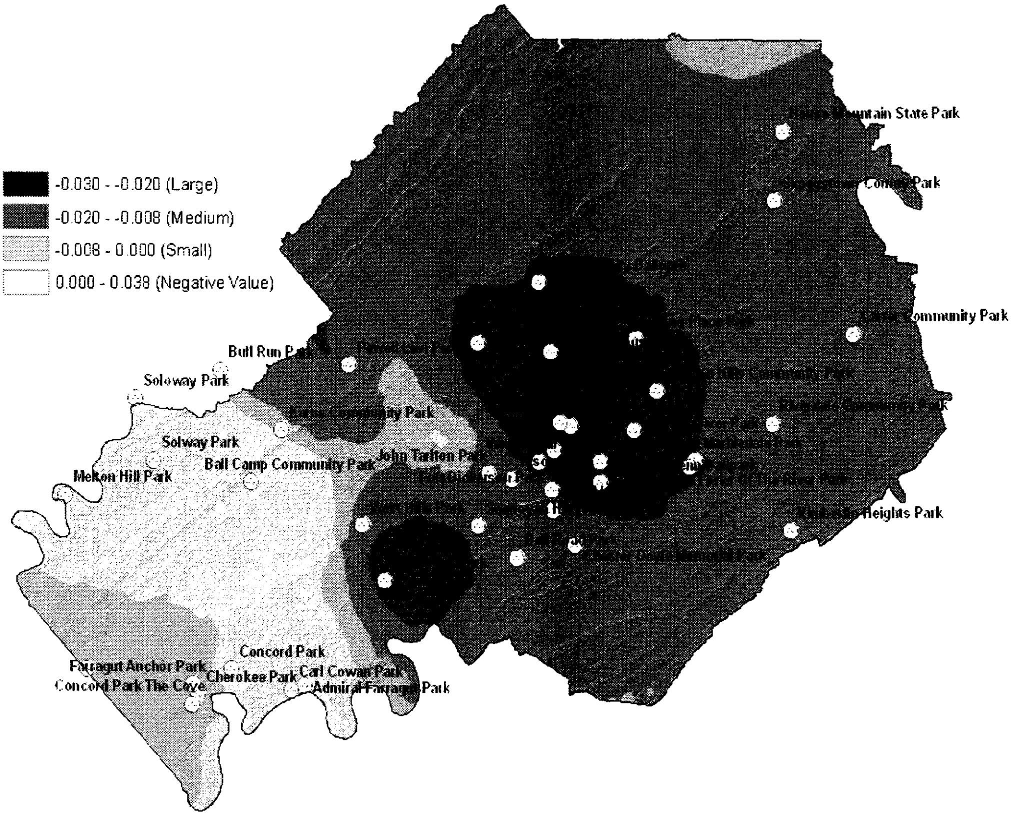

Figure 3. Spatial distribution of marginal effect of distance to nearest park on house price

prices of the parks are presented in table 4. The table and figure show that the middle of Knox County with its many city parks, and the county's southwest region near Rocky Hill Park have the largest marginal effects. In contrast, the county's western region has very small to slightly negative marginal effects. This variation may be explained by the substitutability between public and private open space. Most houses in the suburbanizing western region of the county have relatively large lots compared to houses near the center of the county in the city of Knoxville. Households with smaller lots near downtown may value public parks more than do households with larger lots and more open space in the west. In addition, it may be that a significant portion of households near the downtown area do not have private transportation for travel to parks beyond walking distance.

There may be other factors causing the small negative marginal effects for parks in west Knox County. One may be the difficulty of separating the effects associated with parks and water bodies. For example, the parks in the southern end of the cluster of negative value in figure 3 (i.e., Concord Park The Cove, Farragut Anchor Park, Concord Park, Cherokee Park, Admiral Farragut Park, and Carl Cowan Park) are all located along or near the Tennessee River (or Fort Loudon Lake) where mean water body value is high. The high and statistically significant mean water body value of the area may suppress the values of the parks along the water bodies in the model. Another factor may be the type of the park. For example, Ball Camp Community Park and Karns

Table 4. Mean Park Values Using Local Estimates from the Local Model

Park	Mean Marginal Effect	Mean House Price ($)	Mean Park Value ($)	N
Soring Brook Park	-0.008	554,560	840	4
Sequoyah Hills Park	-0.018	205,923	702	426
Rocky Hill Park	-0.014	185,382	491	1,169
Halston Hills Community Park	-0.024	108,017	491	203
Bell Road Park	-0.016	151,873	460	207
Fountain City Ballpark	-0.019	115,449	415	1,710
Island Home Park	-0.026	83,913	413	40
Spring Place Park	-0.024	83,361	379	332
White Springs Park	-0.028	69,542	369	550
Woodbine Avenue Ballpark	-0.028	66,898	355	218
Worlds Fair Park	-0.022	81,877	341	28
Holston River Park	-0.028	64,212	341	70
Inkwood Park	-0.019	92,049	331	1,192
Forks of the River Park	-0.018	92,941	317	72
Tyson Park	-0.017	94,556	304	25
Linden Park	-0.029	52,887	290	91
Riverdale Community Park	-0.016	94,921	288	107
Chester Doyle Memorial Park	-0.017	86,634	279	445
Marbledale Park	-0.020	72,200	273	13
Cal Johnson Park	-0.024	57,857	263	8
Maynard Glenn Ballpark	-0.023	60,079	262	173
Kimberlin Heights Park	-0.016	85,287	259	74
Fort Dickerson Park	-0.021	60,355	240	67
Skaggstown County Park	-0.012	100,536	229	90
Powell Levi Park	-0.012	98,905	225	1,172
Mary Vestal Park	-0.019	60,332	217	70
Big Ridge State Park	-0.012	87,392	199	6
House Mountain State Park	-0.011	94,289	196	197
Carter Community Park	-0.011	83,946	175	41
Mayor Bob Leonard Park	-0.003	238,432	135	552
John Tarlton Park	-0.006	79,279	90	410
West Hills Park	-0.004	111,875	85	1,445
Cherokee Park	-0.002	200,344	76	62
Concord Park The Cove	-0.001	335,491	64	86
Farragut Anchor Park	-0.001	184,198	35	527
Karns Community Park	0.000	129,677	0	346

(continued . . .)

Table 4. Continued

Park	Mean Marginal Effect	Mean House Price ($)	Mean Park Value ($)	N
Concord Park	0.002	152,342	-58	760
Bull Run Park	0.003	119,863	-68	42
Admiral Farragut Park	0.002	194,113	-74	667
Carl Cowan Park	0.003	185,733	-106	365
Melton Hill Park	0.006	205,291	-233	35
Soloway Park	0.021	90,283	-359	8
Solway Park	0.020	147,417	-558	210
Ball Camp Community Park	0.028	124,871	-662	1,020

Notes: The mean park value is the marginal implicit price for reducing the distance to the nearest park by 1,000 feet, evaluated at the mean house value and an initial distance of one mile.

Community Park are frequently busy with soccer and baseball activities, which may generate concerns of traffic, noise, and safety disamenities.

To examine the volatility of local regression estimates, the local model is estimated using a bandwidth which is 50% larger and 50% smaller than the bandwidth found using the CV approach in estimating equation (2).[5] The median value of the local marginal effects using both 9,602 and 28,806 feet bandwidths of nearest neighboring data points are fairly close to the median estimates using the CV approach that identified an optimal bandwidth of 19,204 nearest neighboring data points. However, with a bandwidth of 28,806 feet, almost no variation across the area exists in the local marginal effects. As the bandwidth widens to 28,806 feet, the spatial heterogeneity captured by locally weighted regression using the CV approach is not captured, and the local estimates are close to those estimated by OLS. This sensitivity analysis emphasizes the tradeoff between a smaller bandwidth that retains the spatial heterogeneity inherent in the variables and the need to produce estimates that vary smoothly over the spatial regions of the study area (larger bandwidth).

Summary and Conclusions

Residential property value premiums resulting from proximity to amenities such as water bodies and parks are measured globally and locally at the individual level within the Knox County, Tennessee, study area. Findings corroborate previous research, establishing that natural and constructed amenities are valuable attributes in housing demand and positively impact sale prices. Moreover, our results suggest hedonic models can be improved by including GIS information pertaining to natural amenities.

Our results also demonstrate the importance of going beyond the global modeling framework when incorporating GIS information into hedonic models. Local values for individual amenity sources are estimated using locally weighted regression by allowing for nonstationarity in the relationships between proximity to water bodies and parks

[5] Estimates using these larger and smaller bandwidths can be obtained from the authors on request.

and sale prices in the hedonic housing price model. The marginal implicit price of proximity to water bodies (1,000 feet closer) was estimated to be \$491 in the global model, but ranged from -\$497 to \$6,032 locally for individual water bodies. The marginal implicit price of proximity to local parks (1,000 feet closer) was estimated to be \$172 in the global model, but ranged from -\$662 to \$840 locally at an individual park level.

Furthermore, the local model reveals some important local differences in the effects of proximity to water bodies and parks on housing price. The local parameter estimates of proximity to both water bodies and parks have different signs in different regions of the county. These different relationships are obscured in the global model. Without the results from the locally weighted regression model, the variation in effects associated with individual water bodies and parks on housing prices would not be captured.

Estimates of the value of proximity to water bodies and parks, such as those generated in this study, should prove useful as input to future debates about public initiatives to protect open space, whether through ballot measures or other means. The estimated values from locally weighted regression models for individual sources of these amenities can be used for budget decisions regarding resource management or in prioritizing specific water resources and parks to be protected. For example, assessing the added value of a given local park to proximal homes and the resulting level of tax revenues could prove useful to planners trying to justify maintenance expenditures in increasingly tight times. A future research effort could involve examination of values identified within the present modeling framework along with attribute bundles of specific parks or water bodies to identify potential management issues. Moreover, with a sufficiently large set of parks, models could be developed wherein park values are regressed on park attributes to quantify attributes with the highest marginal benefits.

While the hedonic property price method can be used to estimate the value of some non-market goods and services, it is important to remember that the method provides only a limited measure of total economic benefits. For example, water bodies may provide many services in addition to positive amenities for residential property located in proximity to water bodies. These may include biodiversity, water recharge and discharge, and recreation. Parks also provide recreation to people from outside the immediate area. The value of these services may not be fully reflected in residential house prices. House prices also do not reflect benefits received by businesses, renters, and visitors. For these reasons, estimates from hedonic house price models will generally underrepresent the true value of these amenities.

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